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EXAMINER	
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Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	Application No. 10/656,067	Applicant(s) YADEGAR ET AL.	
	Examiner Adrian L. Kennedy	Art Unit 2121	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on *15 August 2006*.

2a)☒ This action is **FINAL**. 2b)☐ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) *7-36,43 and 44* is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) *7-36,43 and 44* is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☒ The specification is objected to by the Examiner.

10)☐ The drawing(s) filed on _____ is/are: a)☐ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)

2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)

3) ☒ Information Disclosure Statement(s) (PTO/SB/08) Paper No(s)/Mail Date *8/15/06*.

4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .

5) ☐ Notice of Informal Patent Application

6) ☐ Other: _____.

Examiner's Detailed Office Action

1. **Claims 1-47** were originally presented.

2. **Claims 1-6, 36-42, 45, 46, and 47** were cancelled.

3. **Claims 7, 17, 20, 25, 34, 43, and 44** were amended.

4. **Claims 7-36, 43 and 44** will be treated on the merits below.

Objections to the Specification

5. The amendment filed August 15, 2006 is objected to under 35 U.S.C. 132(a) because it introduces new matter into the disclosure. 35 U.S.C. 132(a) states that no amendment shall introduce new matter into the disclosure of the invention. The added material which is not supported by the original disclosure is as follows:

> Modern personal computers often have several components, including: a display, a motherboard, a CPU (microprocessor) or other instruction-processing system, primary storage (RAM), expansion cards, a power supply, an optical disc drive, secondary storage (HD or hard disk/drive), a keyboard, and a mouse. As computers are machines for manipulating data according to a list of instructions known as a program, they can take almost any form and be imbedded in a variety of machines including camera, toys, etc. Such computers are now well-known in the art.

Applicant is required to cancel the new matter in the reply to this Office Action.

Claim Rejections - 35 USC § 112

6. The following is a quotation of the first paragraph of 35 U.S.C. 112:

> The specification shall contain a written description of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same and shall set forth the best mode contemplated by the inventor of carrying out his invention.

Claims 7-36, 43, and 44 are rejected under 35 U.S.C. 112, first paragraph, as failing to comply with the written description requirement. The claim(s) contains subject matter which

was not described in the specification in such a way as to reasonably convey to one skilled in the relevant art that the inventor(s), at the time the application was filed, had possession of the claimed invention. Claims 7, 25, 43, and 44 all make mention of a “data storage system”, and “storing compressed data in the data storage system”. Having read the applicants’ entire disclosure, the examiner finds no support for a “data storage system”, and thus considers the “data storage system” to be non-enabled by the specification and new matter in the claims.

Additionally claims 25 and 44 contain a term “energy”. This term appears multiple times in the Specification. It is usual for “energy” to be used in relation to physical activity. The specification does not explain what “energy” means as a term being used in a compression algorithm.

Claim Rejections - 35 USC § 101

7. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

Claims 7-36, 43, and 44 are rejected under 35 U.S.C. 101 because the claimed invention is directed to non-statutory subject matter. Without the inclusion of a data storage system applicants’ invention as claimed is <u>not</u> considered to be directed to patent eligible subject matter.

Claims 7-24 and 43 are directed towards a method of modeling data. Such method represents an abstract algorithm. Abstract ideas (see Warmerdam, 33 F.3d at 1360, 31 USPQ2d at 1759) or mere manipulations of abstract ideas (see Schrader, 22 F.3d at 292-93, 30 USPQ2d at 1457-58) are not patentable. However, for claims including such excluded subject matter to be

eligible, the claims must be for a practical application of the idea. Such practical application can be identified in the following ways:

a. The claimed invention "transforms" an article of physical object to a different state or thing.

b. The claimed invention otherwise produces a useful, concrete and tangible result.

The acts of tessellation, filtering and other disclosed data manipulations do not produce any physical transformations. The next step would be to determine whether the claimed invention produces a useful, concrete and tangible result. Result of the claims is data. Such result is abstract and, therefore, cannot satisfy the condition of being tangible.

Claims 25-36 and 44 are directed towards method for compressing data. Similarly to the method of modeling data, these claims describe mathematical algorithm of transforming data. According to the analysis give above, these claims are also non-statutory as being directed to manipulation of abstract ideas.

Claims 7-36, 43, and 44 do not set forth a "useful, concrete and tangible result". In particular, in it is not considered that these claims set forth a tangible result. Claims 7-36, 43, and 44 do not produce a practical real world result. Claims 7-36, 43 and 44 appear to be nothing more than an abstract algorithm which is not statutory.

Claim Rejections - 35 USC § 102

8. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

A person shall be entitled to a patent unless –

> (b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.
>
> (e) the invention was described in (1) an application for patent, published under section 122(b), by another filed in the United States before the invention by the applicant for patent or (2) a patent granted on an application for patent by another filed in the United States before the invention by the applicant for patent, except that an international application filed under the treaty defined in section 351(a) shall have the effects for purposes of this subsection of an application filed in the United States only if the international application designated the United States and was published under Article 21(2) of such treaty in the English language.

9. Claims 7-17, 24-32 and 36 are rejected under 35 U.S.C. 102(e) as being anticipated by Bright (USPN 6,897,977).

Regarding claim 7:

Bright teaches

(currently amended) A method for modeling data using adaptive pattern-driven filters comprising:

providing a data storage system (col. 13, lines 27-34; disclosed as mass memory storage devices);

providing a linear adaptive filter adapted to receive data and model the data that have a low to medium range of intensity dynamics (col. 3, lines 54-58; disclosed as the part of the algorithm that perform subdivision into triangles);

providing a non-linear adaptive filter adapted to receive the data and model the data that have medium to high range of intensity dynamics (col. 6, lines 1-13; disclosed as the part of the algorithm that performs patters recognition to map texture); and

providing a lossless filter adapted to receive the data and model the data not modeled by the linear adaptive filter and the non-linear adaptive filter, including

residual data from the linear and non-linear adaptive filters (col. 7, lines 23-41; using Huffman lossless compression; evidence that LZW and Huffman methods are lossless is provided by "Lossless Data Compression", http://en.wikipedia.org/wiki/Lossless_data_compression); and

storing the compressed data in the data storage system (The examiner takes the position that in teaching the storing of data representing the triangles and the compressing of the images using triangular decomposition it is inherent that the compressed data is stored); whereby

the data may be preserved in compressed form to occupy less storage space (col. 7, lines 25-27).

Regarding claim 8:

Bright teaches

(original) A method for modeling data as set forth in Claim 7, wherein the linear adaptive filter further comprises: tessellation of the data (col. 4, lines 42-47).

Regarding claim 9:

Bright teaches

(original) A method for modeling data as set forth in Claim 8, wherein the tessellation of the data further comprises: tessellation of the data as viewed from computational geometry (col. 4, lines 42-54; since the tessellation is done using a geometric algorithm, it belongs to computational of algorithmic geometry).

Regarding claim 10:

Bright teaches

(original) A method for modeling data as set forth in Claim 8, wherein the tessellation of the data is selected from the group consisting of planar tessellation and spatial (volumetric) tessellation (col. 5, lines 8-17; disclosed are both forms of tessellation, since each triangle has its own plane with a Z component).

Regarding claim 11:

Bright teaches

(original) A method for modeling data as set forth in Claim 8, wherein the tessellation of the data is achieved by a methodology selected from the group consisting of: a combination of regression techniques; a combination of optimization methods including linear programming; a combination of optimization methods including non-linear programming; and a combination of interpolation methods (col. 5, lines 30-47; disclosed is the use of interpolation)..

Regarding claim 12:

Bright teaches

(original) A method for modeling data as set forth in Claim 10, wherein the planar tessellation of the data comprises triangular tessellation (col. 5, lines 8-17).

Regarding claim 13:

Bright teaches

(original) A method for modeling data as set forth in Claim 10, wherein the spatial tessellation of the data comprises tessellation selected from the group consisting of tetrahedral tessellation and tessellation of a 3-dimensional geometrical shape (col. 5, lines 14-17; each triangle defines a 3-D plane, forming a 3-Dimensional shape. Adjusting 3-D triangles form a tetrahedral).

Regarding claim 14:

Bright teaches

(original) A method for modeling data as set forth in Claim 8, wherein the tessellation of the data is executed by an approach selected from the group consisting of breadth-first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclosed is a depth-first approach), and any method of tessellation that approximates the data subject to an error tolerance (col. 5, lines 49-54; using a similarity threshold).

Regarding claim 15:

Bright teaches

(original) A method for modeling data as set forth in Claim 12, wherein the tessellation of the data is selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition,

any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17).

Regarding claim 16:

Bright teaches

(original) A method for modeling data as set forth in Claim 7, wherein the non-linear adaptive filter further comprises: a filter modeling non-planar parts of the data using primitive data patterns (col. 6 lines 1-9, using a set of predefined texture patterns).

Regarding claim 17:

Bright teaches

(currently amended) A method for modeling data as set forth in Claim 16, further comprising: the modeling of the non-planar parts of the data performed using a methodology selected from the group consisting of: artificial intelligence; machine learning; knowledge discovery; data mining; and pattern recognition (col. 6, lines 1-13; using pattern recognition).

Regarding claim 24:

Bright teaches

(original) A method for modeling data as set forth in Claim 16, further comprising:

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40);

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58).

Regarding claim 25:

Bright teaches

(currently amended) A method for compressing data, comprising:

providing a data storage system (col. 13, lines 27-34; disclosed as mass memory storage devices);

providing a linear adaptive filter adapted to receive data and compress the data that have low to medium energy dynamic range (col. 3, lines 54-58; disclosed as the part of the algorithm that perform subdivision into triangles);

providing a non-linear adaptive filter adapted to receive the data and

compress the data that have medium to high energy dynamic range (col. 6, lines 1-13; disclosed as the part of the algorithm that performs pattern recognition to map texture patterns);

providing a lossless filter adapted to receive the data and compress the data not compressed by the linear adaptive filter and the non-linear adaptive filter; such that data is being compressed for purposes of reducing its overall size (col. 7, lines 23-41; using Huffman lossless compression); and

storing the compressed data in the data storage system (The examiner takes the position that in teaching the storing of data representing the triangles and the compressing of the images using triangular decomposition it is inherent that the compressed data is stored); whereby

the data may be preserved in compressed form to occupy less storage space (The examiner takes the position that the compression of data, for the purpose of the data occupying less space, is inherent in the invention of Bright).

Regarding claim 26:

Bright teaches

(original) A method for compressing data as set forth in Claim 25, wherein the linear adaptive filter further comprises: tessellation of the data (col. 4, lines 42-47).

Regarding claim 27:

Bright teaches

(original) A method for compressing data as set forth in Claim 26, wherein the tessellation of the data is selected from the group consisting of planar tessellation and spatial tessellation (col. 5, lines 8-17; disclosed are both forms of tessellation, since each triangle has its own plane with a Z component).

Regarding claim 28:

Bright teaches

(original) A method for compressing data as set forth in Claim 27, wherein the planar tessellation of the data comprises triangular tessellation (col. 5, lines 8-17).

Regarding claim 29:

Bright teaches

(original) A method for compressing data as set forth in Claim 27, wherein the spatial tessellation of the data comprises tetrahedral tessellation (col. 5, lines 14-17; each triangle defines a 3-D plane, forming a 3-dimensional shape. Adjusting 3-D triangles form a tetrahedral).

Regarding claim 30:

Bright teaches

(original) A method for compressing data as set forth in Claim 26, wherein the tessellation of the data is selected from the group consisting of breadth-first, depth-first, best-first, any, combination of these (col. 6, lines 34-35; disclose a depth-first approach),

and any method of tessellation that approximates the data filtered by the linear adaptive filter within selectably acceptable limits of error (col. 5, lines 49-54; using a similarity threshold).

Regarding claim 31:

Bright teaches

(original) A method for compressing data as set forth in Claim 28, wherein the tessellation of the data is selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17).

Regarding claim 32:

Bright teaches

(original) A method for compressing data as set forth in Claim 25, wherein the non-linear adaptive filter further comprises: a filter modeling non-planar parts of the data using primitive image patterns (col. 6, lines 1-9, using a set of predefined texture patterns).

Regarding claim 36:

Bright teaches

(original) A method for compressing data as set forth in Claim 32, further comprising:

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40);

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58).

Claim Rejections - 35 USC § 103

10. The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

11. Claims 18-23, 33-35, and 43-44 are rejected under 35 U.S.C. 103(a) as being unpatentable over Bright (USPN 6,897,977) in view of Tsishkou et al. ("Mosaic Ultrasound Medical Image Compression Using TTA10 Algorithm").

Regarding claim 18:

Bright teaches a method for modeling data as set forth in claim 16.

Bright does not expressly teach further comprising: training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive filter; and at run-time application of the non-linear adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving.

Tsishkou teaches the training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive filter; and at run-time application of the non-linear adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10; the filter is self-improving by training a tree used for image classification).

Bright and Tsishkou are analogous art since they are both in the field of image compression. At the time of invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10). The reason for doing so would be to assist in working with large numbers of training images (Tsishkou, page 1174, left column, lines 10-14). Therefore, it would have been obvious to modify Bright in view of Tsishkou by using a learning algorithm with a hierarchical tree data structure for pattern-recognition.

Regarding claim 19:

Bright teaches a method for modeling data as set forth in claim 16.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information.

Tsishkou teaches that the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; the data structure is disclosed as a tree based on tessellation).

At the time of invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Regarding claim 20:

Bright teaches a method for modeling data as set forth in claim 16.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; an the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support

vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; and principle component analysis.

Tsishkou teaches that non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; and principle component analysis (page 1175, right column, lines 6-11; tree used for classification is a decision tree).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a patter-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as claim 18 above.

Regarding claim 21:

Bright teaches

> (original) A method for modeling data as set forth in Claim 20, wherein the hierarchy of learning units provide machine intelligence (col. 6, lines 1-9; use of pattern-matching algorithms implies machine learning, *i.e.* a machine has learned to recognize specific image patterns).

Regarding claim 22:

Bright teaches

(original) A method for modeling data as set forth in Claim 20, wherein the primitive data patterns include a specific class of data(col. 6, lines 1-9, using a set of predefined texture patterns; pattern-recognition implies classification , which inherently uses data that belongs to a specific class).

Regarding claim 23:

Bright teaches

(original) A method for modeling data as set forth in Claim 22, wherein the specific class of data is selected from the group consisting of: 2-dimensional data; 3-dimensional data; and N-dimensional data where N is greater than 3(col. 6, lines 1-4; texture patterns are 2-dimensional data).

Regarding claim 33:

Bright teaches a method for compressing data as set forth in claim 32.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellation with the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information.

Tsishkou teach the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for

processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; data structure is disclosed as a tree based on tessellation).

At the time of the invention, it would have obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, line 6-10) and use it as a patter-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Regarding claim 34:

Bright teaches a method for compressing data as set forth in claim 32.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; and principle component analysis.

Tsishkou teaches that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; and principle component analysis (page 1175, right column, lines 6-11; the tree used for classification is a decision tree).

At the time of invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a patter-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Regarding claim 35:

Bright teaches

(original) A method for compressing data as set forth in Claim 34, wherein the primitive data patterns include a specific class of images (col. 6, lines 1-9, using a set of predefined texture patterns; pattern-recognition of images implies classification, which inherently uses data that belongs to a specific class of images).

Regarding claim 43:

Bright teaches

(currently amended) A method for modeling data using adaptive pattern-driven filters (Abstract, modeling is disclosed as compressing data), comprising:

providing a data storage system (col. 13, lines 27-34; disclosed as mass memory storage devices);

applying an algorithm to data to be modeled based on an approach selected from the group consisting of: computational geometry (col. 4, lines 42-47; disclosed as

a compression algorithm that works by geometrically splitting the image); artificial intelligence; machine learning; and data mining;

the data to be modeled selected from the group consisting of: 2-dimensional still images; 2-dimensional still objects; 2-dimensional time-based objects; 2-dimensional video; 2-dimensional image recognition; 2-dimensional video recognition; 2-dirriensional image understanding; 2-dimensional video understanding; 2-dimensional image mining; 2-dimensional video mining; 3-dimensional still images; 3-dimensional still objects; 3-dimensional time-based objects; 3-dimensional object recognition; 3-dimensional image recognition; 3-dimensional video recognition; 3-dimensional object understanding; 3-dimensional object mining; N-dimensional objects where N is greater than 3; N-dimensional time-based objects; sound patterns; voice patterns (col. 4, lines 42-47; compressing video image data); generic data of generic nature wherein no specific characteristics of the generic data are known to exist within different parts of the data (col. 3, lines 7-10; disclosed as compressing general image data comprising of pixels arranged in a grid); and class-based data of class-based nature wherein specific characteristics are known to exist within different parts of the class-based data, the specific characteristics enabling advantage to be taken in modeling the class based data (col. 6, lines 1-13; images having a "textured" appearance, classification matches repeated patterns of pixels);

an overarching modeling meta-program generating an object-program for the data; the object-program generated by the meta-program selected from the group

consisting of: a codec, a modeler, and a combination of both (col. 8, lines 9-15; a color encoding model implies a codec for compressing-decompressing colors);

the data is modeled to enable the data being compressed for purposes of reducing overall size of the data (col. 1, lines 12-17);

the algorithm applied to the data including providing a linear adaptive fitter adapted to receive data and model the data that have a low to medium range of intensity dynamics (col. 3, lines 54-58; disclosed as part of the algorithm that performs subdivision into triangles), providing a non-linear adaptive filter adapted to receive the data and model the data that have medium to high range of intensity dynamics (col. 6, lines 1-13; disclosed as part of the algorithm that performs pattern recognition to map texture patterns), and providing a lossless filter adapted to receive the data and model the data not modeled by the linear adaptive filter and the non-linear adaptive filter, including residual data from the linear and non-linear adaptive filters (col. 7, lines 23-41; Huffman lossless compression);

linear adaptive filter including tessellation of the data including tessellation of the data as viewed from computational geometry (col. 4, lines 42-54; since the tessellation is done using a geometric algorithm, it belongs to computational or algorithmic geometry), the tessellation of the data selected from the group consisting of planar tessellation and spatial (volumetric) tessellation (col. 5, lines 8-17; disclosed are both forms of tessellation, since each triangle has its own plane with a Z component);

the planar tessellation including triangular tessellation (col. 5, lines 8-17);

the spatial tessellation of the data comprises tessellation selected from the group consisting of tetrahedral tessellation and tessellation of a 3-dimensional geometrical shape (col. 5, lines 14-17; each triangle defines a 3-d plane, forming a 3-dimensional shape. Adjusting 3-d triangles form a tetrahedral);

the tessellation of the data achieved by a methodology selected from the group consisting of: a combination of regression techniques; a combination of optimization methods including linear programming; a combination of optimization methods including non-linear programming; a combination of interpolation methods (col. 5, lines 30-47; disclose the use of interpolation);

the tessellation of the data executed by an approach selected from the group consisting of breadth-first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclose a depth first approach), and any method of tessellation that approximates the data subject to an error tolerance (col. 5, lines 49-54; using a similarity threshold);

the tessellation of the data is selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17);

the non-linear adaptive filter including a filter modeling non-planar parts of the data using primitive data patterns including a specific class of data selected from the group consisting of: 2-dimensional data; 3-dimensional data; N-dimensional

data where N is greater than 3 (col. 6, lines 1-4; texture patterns are 2-dimensional data);

the modeling of the non-planar part of the data performed using a methodology selected from the group consisting of: artificial intelligence; machine learning; knowledge discovery; mining; and pattern recognition (col. 6, lines 1-13; using pattern recognition)

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40); and

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58); whereby

the data is modeled to enable better manipulation of the data (col. 2, lines 52-55).

storing the compressed data in the data storage system (The examiner takes the position that in teaching the storing of data representing the triangles and the

compressing of the images using triangular decomposition it is inherent that the compressed data is stored); whereby

the data may be preserved in compressed form to occupy less storage space (The examiner takes the position that the compression of data, for the purpose of the data occupying less space, is inherent in the invention of Bright).

Bright does not expressly teach the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of tessellation for processing being higher according to higher availability of the available information, and including a hierarchy of learning units based on primitive data patterns, the hierarchy of learning units providing machine intelligence, the learning units integrating clusters selected from the group consisting of neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; and principle component analysis;

training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive; at run-time application of the adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving.

Tsishkou teaches the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-

11; the data structure is disclosed as a tree based on tessellation), and including a hierarchy of learning units based on primitive data patterns (page 1174, Fig. 3, mosaic blocks from the indexed database), the hierarchy of learning units providing machine intelligence, the learning units integrating clusters selected from the group consisting of neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; and principle component analysis (page 1175, right column, lines 6-11; the tree used for classification is a decision tree);

training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive; at run-time application of the adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10; the filter is self-improving by training a tree used for image classification).

At the time of invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Regarding claim 44:

Bright teaches a method for compressing data, comprising:

providing a data storage system (col. 13, lines 27-34; disclosed as mass memory storage devices);

providing a linear adaptive filter adapted to receive data and compress the data that have low to medium energy dynamic range, the linear adaptive filter including tessellation of the data (col. 3, lines 54-58; disclosed as the part of the algorithm that performs subdivision into triangles);

the tessellation of the data selected from the group consisting of planar tessellation and spatial tessellation, wherein the planar tessellation of the data comprises triangular tessellation (col. 5, lines 8-17) and wherein the spatial tessellation of the data comprises tetrahedral tessellation (col. 5, lines 14-17; each triangle defines a 3-d plane, forming a 3-dimensional shape. Adjusting 3-d triangles form a tetrahedral);

the tessellation of the data selected from the group consisting of breadth first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclose a depth-first approach), and any method of tessellation that approximates the data filtered by the linear adaptive filter within selectably acceptable limits of error (col. 5, lines 49-54; using a similarity threshold);

the tessellation of the data selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17);

providing a non-linear adaptive filter adapted to receive the data and compress the data that have medium to high energy dynamic range (col. 6, lines 1-13; disclosed

as the part of the algorithm that performs pattern recognition to map texture patterns);

the non-linear adaptive filter including a filter modeling non-planar parts of the data using primitive image patterns, the primitive image patterns including a specific class of images (col. 6, lines 1-9, using a set of predefined texture patterns);

providing a lossless filter adapted to receive the data and compress the data not compressed by the linear adaptive filter and the non-linear adaptive filter (col. 7, lines 23-41; using Huffman lossless compression);

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40);

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58); and

storing the compressed data in the data storage system (The examiner takes the position that in teaching the storing of data representing the triangles and the compressing of the images using triangular decomposition it is inherent that the compressed data is stored); whereby

the data may be preserved in compressed form to occupy less storage space (The examiner takes the position that the compression of data, for the purpose of the data occupying less space, is inherent in the invention of Bright).

Bright does not expressly teach the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information;

the non-linear adaptive filter including a hierarchy of learning units based on primitive data patterns, the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis;

Tsishkou teaches the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; the data structure is disclosed as a tree based on tessellation);

the non-linear adaptive filter including a hierarchy of learning units based on primitive data patterns, the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis (page 1175, right column, lines 6-11; the tree used for classification is a decision tree).

At the time of invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Response to Arguments

Applicant's arguments filed on July 28, 2006 have been fully considered but they are not persuasive. The unpersuasive arguments made by the Applicant are stated below:

In reference to Applicant's argument:

> Applicants have removed the term "3-dimensional video" from their claims. The term "energy is generally known in the art with regards to intensity or other optical characteristics of a pixel, picture element, or image element. The term "intensity" is generally well-known in the art as is reflected by the Bright '977 patent.

Examiner's response:

The examiner takes the position that the statement by the applicants that the terms "energy" and "intensity" are "generally well-known" is not sufficient enough to provide the disclosure based support required to overcome the rejection under 35 U.S.C. 112. Additionally,

the examiner finds that the applicants' reliance on the Bright '977 patent for support of applicants' claimed invention further evidence that the terms "energy" and "intensity" are not substantially supported by the applicants' disclosure. Furthermore applicants' argument are found to be non-persuasive.

In reference to Applicant's argument:

> The examiner rejected certain of the claims under 35 USC § 101 as the claimed invention was considered by the examiner to be directed to non-statutory subject matter. The amendments to the claims are believed to resolve this rejection by further clarification of Applicants' claimed subject matter. It is believed that the State Street case (149F.3d 1368, 47 USPQ 2[nd] 1596 (Fed.Cir.)) is applicable. Applicable particularly point out the utility of being able to provide dat[a] in compressed form so that it occupies less storage space in a storage medium, electronic or otherwise. Furthermore, tangibility of Applicants' claimed invention is present in the testability, detectability, reliability, and controllability of the resulting compressed data as stored in storage system.

Examiner's response:

Regarding independent claims 7 (not argued), 25 (not argued), 17, 43 and 44 (not argued), the examiner maintains the prior rejection under 35 U.S.C. 101. The applicant argues that the "tangibility of the claimed invention is present in the testability, detectability, reliability, and controllability of the resulting compressed data". The examiner takes the position that the testing, detecting, controlling and determination of the reliability of compressed data are all simply data manipulations. This is apparent in the fact that none of the aforementioned manipulations result in a "useful, concrete, **and** tangible result" as established in the State Street case.

Additionally, the examiner takes the position that the modeling of data without a use for said model is equivalent to a non-functional collection of data/algorithms without a use and is non-statutory per se. Furthermore, the combining of non-functional data/algorithms with a

statutory device without the data/algorithm producing a useful, concrete and tangible result does not meet the requirements for patentability under 35 USC 101 or the requirement for a "useful, concrete, and tangible result" as established by State Street.

In reference to Applicant's argument:

> 1.1 Filter 1 treats the quasi-uniform regions in the image using on-line regression learning methods. In contrast, the Bright '977 patent offers an experimentally and theoretically verified inferior data-drive (non-learnable) method of linear interpolation method.

Examiner's response:

The examiner takes the position that Bright '977 teaches the on-line regression learning method as claimed in the applicant's invention. The examiner asserts that the quasi uniform regions as argued by that applicant are equivalent to the increasingly smaller triangles as taught by Bright '977 in Column 2, lines 63-67. The examiner's assertion is additionally supported by the broadest reasonable interpretation of the applicants' claims when read in light of the applicant's specification which discloses that the first filter "implements a triangular decomposition of a 2-dimensional surfaces" which is equivalent to the method taught by Bright '977. Additionally, Bright' teaches the use of pattern recognition algorithm for learning (Column 6, Lines 4-9), which anticipates the adaptive method claimed by the applicant. Furthermore, applicants' arguments are found to be non-persuasive.

In reference to Applicant's argument:

> 1.2 Filter 2 treats the piecewise extended and organized structures in the image using on-line and off-line adaptive non-linear regression learning methods. In contrast, the Bright '977 patent does not at all offer any method for treating piecewise extended organized structures.

Examiner's response:

The examiner takes the position that the extended organized structures in the image are the increasingly smaller triangles as taught by Bright '977 in Column 2, lines 63-67. This position is supported by the applicants' disclosure which teaches the Paragraph 0099 which discloses the triangular decomposition stages being varied by shrinking the triangles by half. Therefore, applicants' arguments are found to be non-persuasive.

In reference to Applicant's argument:

> 1.3 Filter 3 treats the texture structures in the image using on-line and off-line adaptive non-linear regression learning methods to efficiently compress texture pattern. In contrast, the Bright '977 patent only suggests in brief passing a template matching method that requires large database of texture patterns and an extremely efficient search mechanism for texture pattern matching none of which are at all discussed in the Bright '977 patent.

Examiner's response:

The examiner takes the position that the LZW compression method is equivalent to the applicants' filter 3. This is apparent in the fact that the applicants' disclosure which states in Paragraph 0084 that Filter 3 is a statistical coding method. Therefore, the applicants' arguments are found to be non-persuasive.

In reference to Applicant's argument:

> 2. Yadegar et al apply lossless adaptive on-line preconditioning/learning arithmetic coding to the residuals from Filter 1, Filter, and Filter 3 each separately for optimal last drop compression. In contrast, in the Bright '977 patent there is no mention of lossless coding to the residuals.

Examiner's response:

The examiner previously established that Bright '977 taught the Filters 1, 2, and 3. Additionally, although not explicitly recited, Bright '977 teaches the lossless coding of the

residuals by stating that strings are encoded using well-known lossless compression algorithms like LZW and Huffman in Column 7, Lines 37-41 as evidenced by the Wikipedia citation to define what LZW and Huffman are.. Therefore, the applicants' arguments are found to be non-persuasive.

In reference to Applicant's argument:

> Applicants have conducted extensive experimentation on linear interpolation, linear regression and non-linear regression methods. Experiments strongly favor regression methods over linear interpolation, though for quasi-uniform regions enhancements obtained by the application of non-linear regression over linear regression is small. For this reason Applicants have abandoned applying linear interpolation, which is a technique adopted Bright, and have selected linear regression method over non-linear regression methods because of its computational efficiency.

Examiner's response:

The examiner has considered this argument and takes the position that because the claims which are currently pending in the amended application make use of "interpolation methods", that Bright '977 anticipates applicants' claimed invention.

In reference to Applicant's argument:

> The Tsishkou et al algorithm shows wide divergence from Applicants' algorithm. Tsishkou et al algorithm is strongly class based whereas Applicants algorithm can be made to be generic or class based depending on the specific application. Tsishkou et al algorithm requires off-line generation of a hierarchical database of indices whereas Applicants algorithm requires on-line and off-line linear and non-linear regression machine learning regime whereby the internal parameters of the learning regime are turned on the basis of the training set – this difference makes Applicants' method far more scalable. It is important to note that Applicants' algorithm requires no database of templates of any sort, none whatsoever. Tsishkou et al algorithm requires construction of an explicit, extremely efficient search algorithm, for template matching whereas Applicants' machine learning paradigm totally overcomes the search hurdle since during training and adjustment of the internal parameter of the learning regime, a mapping is established between the training set and the output of the learning regime so that at run-time this mapping is spontaneously activated for a match. Tsishkou et al. do not spell out any specific decomposition scheme: Whether triangular or rectangular? Binary, quaternary, ternary or what? The caption of Figure 1 in Tsishkou et al publication states segmentation based on polar coordinates. Yadegar et al's algorithms are not specific to polar of Cartesian coordinate systems and they have been applied to a variety of triangular decomposition techniques. Tsishkou et al do not spell out the specific lossless coding method other than stating they apply

> entropy coding. Applicants have applied a variety of lossless coding methods such as differential coding, run length coding, Huffman coding, arithmetic coding and adaptive arithmetic coding. Applicants' experiments demonstrate adaptive arithmetic coding to be superior.

Examiner's response:

First, applicants' arguments are more specific than the claims. However, even if the claims were amended to state that the algorithm were classless, the examiner takes the position that both the algorithm of Tsishkou and Applicants are class based, where the class is based on the image classification determined during the learning phase of both algorithms for the purpose of providing better image segmentation/decomposition. Additionally, regarding the applicants' other arguments directed towards Tsishkou, the examiner takes the position that if considered only on its own merits, Tsishkou et al would not teach the topics argued. However, Bright '977 does teach the parts of Applicants' invention which were not taught in Tsishkou.

Furthermore, considering that Bright '977 teaches a method of compressing pictures and video, and Tsishkou et al teaches a method of compressing an image based on the learned (via training) class of the image, the examiner asserts that the two algorithms are analogous in the art of image/video compression, and that the two references can be combined without destroying the other reference.

Therefore, applicants' arguments in relation to Tsishkou are found to be non-persuasive.

Conclusion

In the examiner would like to remind the applicant that claims are read in light of the specification, but limitations expressed in the specification are not read into the claims. The applicants' remaining arguments were made on the basis of applicants' disclosed invention

whereas said arguments should have been directed towards applicants' claimed invention. However, the examiner has thoroughly considered the applicants' arguments in relation to applicants' claimed invention and has come to the conclusion that the applicants' arguments are found to be non-persuasive in light of the claimed invention.

The prior art made of record and not relied upon is considered pertinent to applicant's disclosure. Hoffberg et al. (USPN 5,875,108) is cited for his ergonomic man-machine interface incorporating an adaptive pattern recognition based control system. Kawanaka (USPN 6,791,543) is cited for his method of forming and structuring polygonal mesh data. Yokose et al. (USPN 6,782,133) is cited for is image encoding and decoding apparatus. Lengyel (USPN 6,614,428) is cited for his compression of animated geometry using a hierarchical level of detail coder.

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Adrian L. Kennedy whose telephone number is (571) 270-1505. The examiner can normally be reached on Mon -Fri 8:30am-5pm.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Anthony Knight can be reached on (571) 272-3687. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

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